Stochastic modeling and optimization of photovoltaic systems using probabilistic profiles of demand and solar radiation with HOMER Pro

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Abstract: The study involves the integration of stochastic modeling and optimization of the on-grid photovoltaic (PV) system with Homer Pro and Python tools. Probabilistic functions were applied, along with 3 metrics (coefficient of determination R^2, Akaike AIC information criterion and Kolmogorov-Smirnov KS test) on consumption data from the Cotopaxi Technical University (UTC). Under the UTC, there was a variation in daily radiation between 3.98 - 4.55 kWh/m²/day, while the monthly demand varied from a minimum equal to 521 kWh to a maximum of 4,529.00 kWh. The results of the optimal photovoltaic system involved several technical aspects, with which it must have a capacity of 6.20 kW, annual production of 6,764.00 and a capacity factor of 9.62%. In relation to the economic aspects, the economic viability of the system was demonstrated by having a levelized cost of energy (LCOE) of 0.085 USD/kWh and a net present cost (NPC) of $47,711.87. This study is essential for modelling the charging behaviour, which improves the robustness of the system which provides solid support for sustainable energy planning.

Keywords: solar energy, stochastic modeling, gamma distribution, energy optimization, HOMER Pro, Python

Received: April 26, 2025. Revised: December 12, 2025. Accepted: March 3, 2025. Published: June 3, 2026.

1 Introduction

The constant increase in electricity consumption and environmental concerns are motivating factors for the use of renewable energies, such as photovoltaic (PV) solar power. When integrated into the electrical grid, methods are needed to simulate the uncertainty surrounding solar irradiance and energy demand [1]. Irradiance exhibits daily (bell-shaped) and seasonal variations due to atmospheric conditions and cloud cover. This variability creates uncertainty in electricity generation, thus requiring a model to address this issue [2].

Variability also occurs in daily electricity consumption. Modeling through probabilistic methods allows this uncertainty to be captured and adjusted more appropriately [3]. According to [4], stochastic approaches are suitable for modeling variability and adapt effectively to real-life situations rather than average conditions. In addition, it must have a synchronization between the two variability parameters mentioned above, to obtain a good efficiency of the PV system [5].

There are several reviews that show topics oriented to PV systems with the application of stochastic models. However, the knowledge conveyed in the present work is generally dispersed across independent thematic lines. On one hand, several studies focus entirely on probabilistic modeling of daytime irradiance using Beta or Weibull distributions [6], [7]. However, some studies use advanced techniques. According to [8], applied stochastic differential equations, which, with random hourly errors, allow intra-hour variations to be captured with high precision. Meanwhile, Monte Carlo–based studies, such as that of [9], demonstrated deviations of 24.4% between estimated and actual energy generation, suggesting the need to evaluate such extreme scenarios in the design and operation of PV systems within distribution networks. Similarly, [10] they estimated a probability of overvoltages from congested PV systems, using risk-based methods for active grids. Authors such as [11], [12] indicated that PV systems and energy demand in low-voltage grids are considered as stochastic processes due to variability.

Currently, there are tools such as HOMER Pro and PVsyst, among others [13]. For example, [9] he used a deterministic model with PVsyst to estimate PV energy production from average irradiances. Therefore, it had limitations at the environmental and operational levels by not considering variability.

To solve this problem, the authors propose a Monte Carlo simulation in order to quantify uncertainty and evaluate the model under real conditions. In addition, they apply simulations with HOMER Pro, which generates a complete technical and economic analysis [14]. These scenarios integrate stochastic models under extreme conditions, which improve PV performance throughout the simulated period [15], [16]. This software also offers sensitivity studies to the use of various technologies, load profiles, and electrical power sources [17].

2 Mathematical Modeling

2.1 Monte Carlo

The Monte Carlo method involves repeated iterations within a mathematical model using random projections to replicate the true variability associated with uncertain parameters. Based on the outcomes of these iterations, the P50 mean (μ), variance (σ^2), uncertainty (standard deviation σ), and a confidence interval (CI) for the projected results are obtained, as illustrated in Equation 1, where [9]:

$$\begin{cases} \mu = \dfrac{1}{N}\sum_{i=1}^{N} X_i \\ \sigma^2 = \dfrac{1}{N-1}\sum_{i=1}^{N}(X_i-\mu)^2 \\ \sigma = \sqrt{\sigma^2} \\ CI = \mu \pm Z\dfrac{\sigma}{\sqrt{N}} \end{cases} \tag{1}$$

- N is the total number of Monte Carlo simulations.
- X_i represents a possible annual production.
- Z is the critical value of the standard normal distribution, which accounts for how many standard deviations σ are around the sample mean $\bar{X}$.

The resulting demand enables an optimal projection of uncertainty, supporting more robust decision-making in the design and planning of energy sources, compared to deterministic methodologies such as linear optimization and single-point approaches [17], [18].

2.2 Load Demand

The electrical demand is represented as a function of the probability distributions designated in Equation 2, where [4], [5], [19], [20]:

- k and c are the shape and scale parameters of the function, respectively.
- α is the shape parameter and β is the rate parameter (=1/ μ).
- λ is the occurrence rate, being the inverse of μ.

$$\begin{cases} f(x) = \dfrac{e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}}{\sigma\sqrt{2\pi}} & \rightarrow Normal \\ f(x) = \dfrac{e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}}}{x\sigma\sqrt{2\pi}} & \rightarrow Log-normal \\ f(x) = \dfrac{k}{c}\left(\dfrac{x}{c}\right)^{k-1} e^{-(x/c)^k} & \rightarrow Weibull \\ f(x) = \dfrac{\beta^\alpha x^{\alpha-1}e^{-\beta x}}{\Gamma(\alpha)} & \rightarrow Gamma \\ f(x) = \lambda e^{\lambda x}; x \geq 0 & \rightarrow Exponential \end{cases} \tag{2}$$

The analysis is primarily conducted using descriptive statistics, mean, standard deviation, and range, to examine the variability of the simulated indicators. In addition, the Kolmogorov–Smirnov (KS) goodness-of-fit test, the Akaike Information Criterion (AIC), and the coefficient of determination (R^2) are employed to calibrate the validity of the distribution functions, as shown in Equation 3, where [21], [22], [23]:

$$\begin{cases} KS = max_{1\leq i\leq n}\left(F(X_i) - \dfrac{i-1}{n}, \dfrac{i}{n} - F(X_i)\right) \\ AIC = -2\ln\left(\mathscr{L}\left(\hat{\theta}_{MLE|X}\right)\right) + 2K \\ R^2 = 1 - \dfrac{RSS}{\sum_{i=1}^{N}(X_i-\mu)^2} \\ RSS = \sum_{i=1}^{N}(X_i - f(t_i,p))^2 \end{cases} \tag{3}$$

- RSS is considered as the residual sum of squares between the actual values X_i and the predicted values $f(t_i,p)$.
- $\mathscr{L}$ represents the likelihood function.
- $\hat{\theta}_{MLE}$ This is the maximum likelihood estimation.
- Therefore, $\mathscr{L}\left(\hat{\theta}_{MLE|X_i}\right)$ is the maximum value of the log-likelihood. These data are experimental, obtained from a probability distribution function depending on the parameters. X_i.
- K denotes the estimated parameters, including the variance.

In this way, the objective is to prioritize those distributions that provide satisfactory fits for positive and asymmetric data, such as the Gamma and Log-normal. Since HOMER Pro supports simulations with uncertainty in some of the most critical variables, it is complemented by sensitivity analyses regarding factors such as variations in system lifetime, discount rate (DR), and system efficiency, all of which influence the economic outcomes.

2.3 Stochastic Optimization

2.3.1 Objective Function

The proposed optimization approach considers the grid-connected photovoltaic system (PV), which minimizes the net present cost (NPC) while meeting the electricity demand. This is expressed in Equation 4, as cited in [19], [24]:

$$\min \mathrm{NPC} = \sum_{n=1}^{N} \frac{C_{cap,n} + C_{rep.n} + C_{O\&M,n} - C_{salv,n}}{(1+DR)^n} \tag{4}$$

- $C_{cap,n}$: capital costs.
- $C_{rep.n}$: replacement costs.
- $C_{O\&M,n}$: operation and maintenance costs.
- $C_{salv,n}$: salvage value.
- N project lifetime cycle.
- DR discount rate.

2.3.2 Input Parameters

When complete hourly records are not available, HOMER generates irradiance values from monthly averages by applying Equation 5 [19]. The algorithm shows a temporal relationship between the hours when the sky is cloudy and clear. Furthermore, the error is less than 5% in relation to the actual data [25].

$$G_{ave} = K_t G_{0,ave} \tag{5}$$

- K_t represents the clearness index.
- G_{ave} y $G_{0,ave}$ indicate the synthetic and extraterrestrial irradiance, respectively.

With the irradiance and demand profiles generated, HOMER Pro performs simulations by combining the input variables. To this end, HOMER Pro applies an iterative Monte Carlo analysis, in which each configuration is evaluated according to a probability distribution that describes the uncertainty. Equation 6 shows the obtaining of the levelized cost of energy (LCOE), where the term CRF is the capital recovery factor [19], [26], [27].

$$\begin{cases} \mathrm{LCOE} = \dfrac{C_{annualized}}{E_{Produced}} = 0{,}085\ \$/\mathrm{kWh} \\ C_{annualized} = \mathrm{NPC} \times \mathrm{CRF}(\mathrm{TD}, \mathrm{N}) \\ \mathrm{CRF}(\mathrm{TD}, \mathrm{N}) = \dfrac{\mathrm{TD}(1+\mathrm{TD})^{N}}{(1+\mathrm{TD})^{N} - 1} \end{cases} \tag{6}$$

2.3.3 Constraints

When designing grid-connected photovoltaic systems (PV), it is essential to estimate technical constraints for the minimum and maximum capacity of the PV array and the inverter size. The system must have an installed capacity such that the maximum photovoltaic power P_{FV} is greater than the load consumption P_{load}, but without oversizing beyond physical or economic limits. Regarding the inverter P_{inv}, it is required that no energy be lost due to saturation and that costs do not increase because of oversizing. As noted by [28], a power sizing ratio (PSR) of approximately 1.19 units is considered, as shown in Equation 7.

$$\begin{cases} P_{load} < P_{PV}, P_{inv} \\ PSR = \dfrac{P_{FV}}{P_{inv}} \\ 1 < PSR \le 1{,}19 \end{cases} \tag{7}$$

2.4 Design of the study

In this study, a quantitative, scientific, descriptive, explanatory, and quasi-experimental approach is followed, since simulations are carried out based on two different scenarios. In addition, computational simulations are used to quantitatively evaluate the effect of stochastic modeling on the technical and economic performance of an on-grid photovoltaic system (PV). The primary software employed is HOMER Pro, while Python code is used to generate hourly demand profiles by incorporating probability distribution functions.

A design procedure is detailed (see Figure 1), which begins with the scenario definition and continues through to the results, as indicated below:

P1. The PV on-grid system present at the UTC has been established as a study. In addition, parameters and conditions such as installed capacity, electricity demand, and climatic conditions are defined.

P2. Solar radiation data were obtained from the NASA-POWER database incorporated into HOMER Pro [29]. From this, the horizontal solar radiation values (GHI, Global Horizontal Irradiance) of the case study are used.

P3. Before running the simulation, demand profiles must be prepared using Python, applying stochastic simulation with probabilistic distribution functions (Gamma, Log-normal, Weibull). These were validated with metrics such as the KS test and AIC. Then, in HOMER Pro, these hourly data are replaced with a customized .csv file.

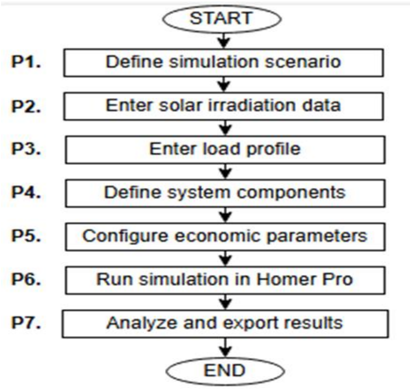

Fig. 1: *Process of design.*
Source: created by the authors.

P4. Three essential components are included: panels, inverters, and controllers. In view of this, efficiency, useful life, annual degradation and costs are defined.

P5. Economic parameters are defined, including the discount rate (DR), inflation, project lifetime *N* (20–25 years), and electricity price based on the tariff schedule (0.085 USD/kWh) according to the resolution of the Electricity Regulation and Control Agency ARCONEL 002/24 [27].

P6. HOMER Pro is capable of performing various combinations of technical/economic origin in order to establish the optimal configuration; with this, NPC and LCOE are minimized.

P7. The results include multiple figures and tables, such as the energy production curve, comparison of deterministic and stochastic scenarios, economic analysis, annual cash flow, and percentage sensitivity to the discount rate or variation in energy price. Graphical and numerical reports are exported for integration into the technical report.

3 Results

3.1 Electricity Consumption

A stochastic projection was carried out to develop the hourly demand profile. This method was based on a Monte Carlo simulation that employed monthly electricity consumption data (see Table 1) from UTC.

Table 1: *Monthly Electricity Consumption at UTC.*

Month	kWh/month	Month	kWh/month
January	521,00	July	4.310,00
February	1.767,00	August	4.529,00
March	3.608,00	September	939,00
April	3.346,00	October	825,00
May	3.873,00	November	965,00
June	3.855,00	December	987,00

Source: created by the authors.

Figure 2 shows the monthly energy consumption in kWh, under rainy (light band) and dry (dark band) seasons in the months of the UTC province, where high consumption is observed from June (3,855 kWh/month) to August (4,529 kWh/month).

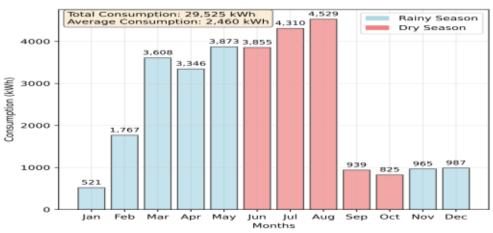

Fig. 2: *Monthly UTC consumption.*
Source: created by the authors.

3.2 Statistical Distribution of Consumption

Figure 3 shows a statistical comparison under the criteria of KS, AIC, projection error and stability, based on Monte Carlo simulations. These are defined under a percentage yield level; among them, the best known is the Normal distribution with 79.3%, closely followed by the Gamma distribution with 79.1%. Both distributions show a very good fit, with a p-value greater than 0.27 and stability above 90%, which demonstrates an acceptable level of consistency in the simulations. In contrast, the Weibull distribution exhibited the lowest performance with 76.6%.

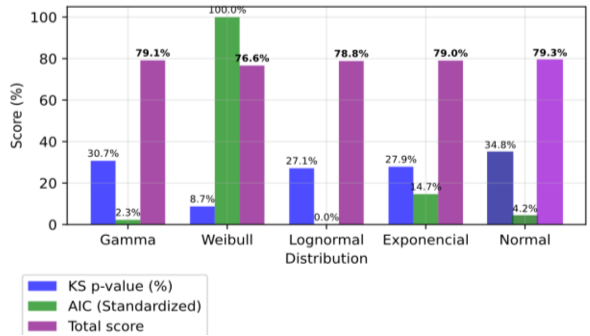

Fig. 3: *Evaluation of Statistical Distributions.*
Source: created by the authors.

3.3 Monte Carlo Simulation

A comparison between the monthly energy consumption values and the stochastic model with Monte Carlo is shown in Figure 4. The average value is identified by the red line, while the shaded band is the P10-P90 percentile ranges and 25% - 75% interquantiles. Therefore, the dispersion of the simulations and their concentration are observed.

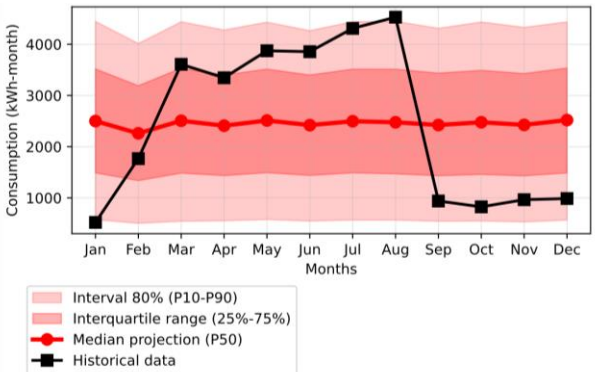

Fig. 4: *Actual Data vs. Monte Carlo Projection.*
Source: created by the authors.

3.4 Solar Radiation at UTC

Table 2 details the monthly values of $K_t y$ and the average daily solar radiation for UTC. It can be observed that the daily values range from a relatively low 3.980 kWh/m²/day recorded in December to

4.550 kWh/m²/day in March, reflecting a consistent availability of solar resources throughout the year. The clearness index K_t fluctuates little between the months of the year, but reaches a maximum of 0.457 in July, while in December it is minimal, with a value of 0.397.

Table 2: *Solar Radiation – UTC.*

Months	K_t	Radiation kWh/m²/day
January	0,408	4,140
February	0,416	4,350
March	0,433	4,550
April	0,426	4,330
May	0,430	4,120
June	0,437	4,020
July	0,457	4,270
August	0,453	4,460
September	0,414	4,270
October	0,408	4,240
November	0,422	4,300
December	0,397	3,980

Source: created by the authors.

3.5 Technical and Economic Grid-Connected PV System

This PV system includes the connection to the electricity grid, converters and load, as shown in Figure 5, whose purpose is to partially supply the energy demand of the UTC. Furthermore, it has a capacity equal to 6.20 kW peak, the value of which has the appropriate adjustment to minimize the Net Present Cost (NPC) without impairing the operation of the system.

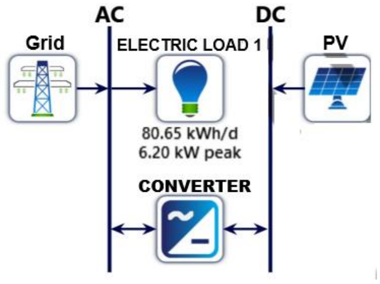

Fig. 5: *Grid-Connected PV System.*
Source: Prepared by the authors.

The NPC has a maximum value of $47,711.87, which is equivalent to the total investment of the project during the entire useful period, as indicated in Figure 6. The LCOE indicates the unit price of generation and is equal to 0.085 USD/kWh. Finally, the annual operating cost is $2,458.19, and the majority value is due to the maintenance of the PV system. Under all these parameters, the proposal is both technically and economically viable.

Fig. 6: *Projected System Costs.*
Source: created by the authors.

Table 3 shows the costs of PV system components for the 25-year project period, for a total value of $21,115.79 and distributed as follows: $20,076.21 for the PV modules and $1,038.58 for the converter. In addition, there are changes for the replacement of the converter for a value of $334.62, operation/maintenance (O&M) costs equal to $22,947.43 in the network and $2,172.10 in PV. It also includes a salvage value at the end of the life cycle, which in this case is negative by $52.42 for the converter, reflecting a negative residual value. Therefore, the NPC is equal to $47,711.87, which represents the total monetary cost at present and helps the implementation and operation of the system throughout the life cycle.

Table 3: *PV System Investment Costs.*

Components	Capital ($)	Replacement ($)	O&M ($)	Salvage ($)	Total ($)
Generic PV	20.076,21	0,00	2.172,10	0,00	**22.248,31**
Grid	0,00	0,00	22.947,43	0,00	**22.947,43**
Others	1,00	0,00	1.081,94	0,00	**1.082,94**
Converter	1.038,58	334,62	112,41	-52,42	**1.433,19**
System	21.115,79	334,62	26.313,88	-52,42	**47.711,87**

Source: created by the authors.

The amortization of the costs for its installation is illustrated in Table 4 and Figure 7, where the economic flow is reflected. Part of the investment ($21,115.79) and over the years, there is an annual operating expense of $2,422.11, which accumulates per year. At year 15, a replacement of the converter is presented, for a value equal to $346.19.

Table 4: *Annual Energy Production.*

Source	kWh/year	%
Generic PV	6.764,00	22.2
Grid Purchase	23.648,00	77.8
Total	**30.412,00**	**100**

Source: created by the authors.

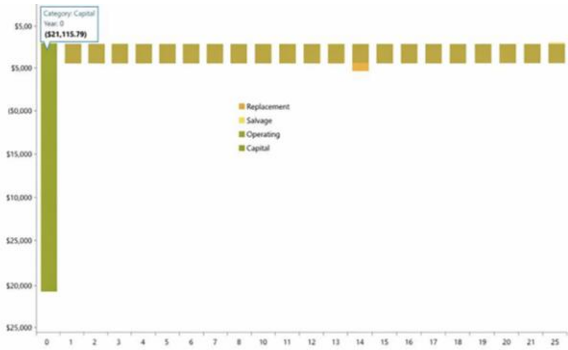

Fig. 7: *Project Amortization.*
Source: created by the authors.

The cumulative cash flow expressed in Figure 8 shows how it changed over the 25-year duration of the PV on-grid project. In year 0, the investment is taken into account, which represents a negative value, since it represents the initial costs of the system. As the years go by, this value decreases due to the savings generated by PV. This type of behavior indicates that the PV system is economically cost-effective and viable for future implementation.

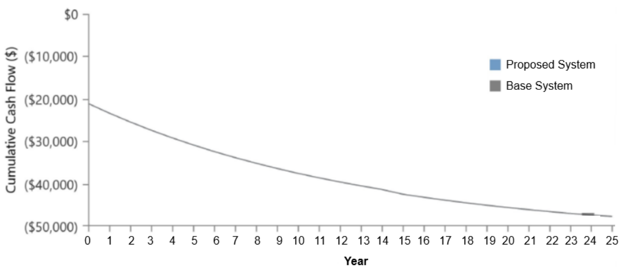

Fig. 8: Cumulative Cash Flows.
Source: created by the authors.

Table 5 describes the production of electrical energy with both the PV system and the purchase of energy. This is divided into 22.2% (6,764.00 kWh/year) with the PV system and the remainder, i.e., 77.8% (23,648.00 kWh/year) were covered by energy purchases from the electricity grid. Therefore, the PV system supplies a little more than a fifth of the UTC's electricity demand; therefore, there is a high dependence on the conventional grid.

Table 5: *Annual Energy Production.*

Source	kWh/year	%
Generic PV	6.764,00	22.2
Grid Purchase	23.648,00	77.8

Source: created by the authors.

A total of 99.5% (29,437.00 kWh/year) corresponds to the primary load consumption in alternating current (AC), which is considered the main energy demand of the system, as shown in Table 6. However, there is also grid-related consumption of 147 kWh/year, or 0.5%, where a small energy surplus is generated.

Table 6: *Annual Energy Consumption of the System.*

Category	kWh/year	%
Primary AC Load	29.437	99,5
Primary DC Load	0	0
Deferrable Load	0	0
Energy Surplus	147	0,5
Total	**29.584**	**100**

Source: created by the authors.

The PV system operates at a nominal capacity equal to 6.20 kW, as in Table 7; in addition, it has an estimated total annual production of 6,764.00 kWh, which is equivalent to an average generation equal to 18.5 kWh per day. In addition, it has an installed capacity factor of 9.62%, 4,380 hours of operation of the PV system per year and has a maximum power of 5.66 kW. The penetration of the on-grid PV system is estimated at 23% of the total demand. Finally, the LCOE stands at $0.085/kWh, with no losses due to cut production, reflecting an efficient benefit from solar energy.

Table 7: *Operational Parameters of the Grid-Connected PV System.*

Parameter	**Value**	**Unit**
Nominal capacity	6,20	kW
Average output	0,772	kW
	18,5	kWh/day
Capacity factor	9,62	%
Total production	6.764,00	kWh/year
Minimum output	0	kW
Maximum output	5,66	kW
PV penetration	23	%
Operating hours	4.380,00	h/year
Levelized cost	0,085	$/kWh
Curtailed production	0	kWh
Annual savings	574,94	$/year

Source: created by the authors.

The PV inverter (converter) has a nominal capacity (maximum output) of 3.46 kW, which operates with 0.678 kW of average power, with a capacity factor of 19.6%, as illustrated in Table 8. During one year of inverter operation, i.e., 4,380 hours, the system generated 5,936.00 kWh of energy, a balance of 6,249.00 kWh or an energy income of 6,249.00 kWh. When calculating, losses of 312 kWh were obtained. This can be represented as a result of energy conversion and overloads.

Table 8: *Inverter and Rectifier Demand and Consumption.*

Parameter		Inverter	Rectifier	Unit
Capacity		3,46	3,46	kW
Output	Average	0,678	0,00	kW
	Minimum	0,00	0,00	kW
	Maximum	3,46	0,00	kW
Capacity factor		19,6	0,00	%
Operating hours		4.380,00	0,00	h/year
Energy output		5.936,00	0,00	kWh/year
Energy input		6.249,00	0,00	kWh/year
Losses		312	0,00	kWh/year

Source: created by the authors.

3.6 Comparison Between Design Methodologies

The authors' proposal is considered to be better than others cited in Table 9 [7], [9], [24] since it integrates stochastic modeling and technical/economic optimization of the on-grid PV system with HOMER Pro. Unlike the aforementioned literature reviews, which employ deterministic approaches, trimmed distributions, or partial validations at the statistical level, the proposal includes multiple probabilistic distributions for solar demand and radiation, with statistical metrics such as p-values, R^2, AIC, and KS, which help to validate uncertainty. Similarly, Monte Carlo simulation allows multiple operating styles and cost scenarios to be compared, resulting in an on-grid PV design in which technical-economic performance is simultaneously optimized.

Table 9: *Comparative Analysis of Previous Studies.*

Aspects	[9]	[7]	[24]	Proposed Approach
Probability distributions (demand and/or radiation)				
Weibull	X	✓	Time series (ARIMA), no statistical distributions	✓
Log-normal	X	X		✓
Normal	✓	X		✓
Gamma	X	X		✓
Exponential	X	X		✓
Statistical metrics				
Mean (P50)	✓	✓	X	✓
Standard deviation	✓	✓	X	✓
Confidence intervals	✓	✓	X	✓
p-value	✓	X	X	✓
R^2	X	X	X	✓
AIC	X	X	✓	✓
KS	X	X	X	✓
MAPE	X	✓	✓	X
Applied methodologies				
Monte Carlo	✓	X	X	✓
Neural networks	X	✓	X	X
Single-point	X	X	✓	X
Application software				
Homer Pro	X	X	X	✓
PVSyst	✓	X	X	X
Matlab	X	✓	✓	X
On-grid PV system designs				
Technical	✓	✓	✓	✓
Economic	X	X	X	✓

Source: created by the authors.

4 Scientific Contribution

The scientific contribution of this research lies in the integration of stochastic modeling into the energy optimization process of photovoltaic systems, using HOMER Pro and Python as complementary simulation tools. This work provides a pioneering methodological scope by representing the variability of solar irradiation and electricity demand through probability distributions, Gamma, Normal, Log-normal, Exponential, and Weibull, which allows for a more precise modeling of the uncertainty present in real systems.

In addition, statistical tests such as R^2, AIC, and the KS test are employed to validate the developed model and its applicability in both academic and practical environments. Finally, this model contributes to the energy sector, establishing a base framework that can be replicated for other educational institutions. Therefore, it is shown as a valid scientific tool in the design of PV systems in uncertainty scenarios.

5 Conclusions

The results presented demonstrate that the stochastic model makes it possible to represent more realistically the daily variability of solar irradiance (3.98 – 4.55 kWh/m²) and the monthly variability of electricity demand (521 – 4,529.00 kWh). In comparison with a classical deterministic model, stochastic models also capture the uncertainty of the natural resource, resulting in grid-connected photovoltaic system configurations that are more robust with respect to meteorological and consumption variability.

The application of Python and HOMER Pro was fundamental for the implementation of the integrated simulation and optimization methodology. In Python, hourly demand profiles were constructed based on different probabilistic distribution densities, whose performances were 79.2% (Gamma), 76.6% (Weibull), 78.7% (Log-normal), 79.2% (Exponential), and 79.3% (Normal), validated with statistical metrics such as R^2, AIC, and KS.

Meanwhile, in HOMER Pro, multiple techno-economic simulations were carried out, guided by the accessible set of configurations that allowed optimization of the Net Present Cost (NPC) at USD 47,711.87 and a Levelized Cost of Energy (LCOE) of USD 0.085/kWh.

HOMER Pro sets several technical factors, such as the optimal capacity of 6.20 kW of the on-grid PV system, along with an annual output equal to 6,764 kWh and a capacity factor of 9.62%. The LCOE results of 0.085 USD/kWh fall within the ARCONEL 002/24 tariff framework. The total NPC of the operation was USD 47,711.87, and operating costs remained stable throughout the years, demonstrating that the system was technically viable and economically profitable, as grid electricity consumption was very low.

AI statement

During the preparation of this article, the authors used AI tools to translate into English.

Acknowledgments

The UTC is thanked for the access to the information of the educational entity, which allowed us to proceed with the present investigation. Also, technical support is paid by teachers. This work was carried out with the help of HOMER Pro and Python software, which are essential in the modeling and simulation of the PV system.

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Contribution of individual authors to the creation of a scientific article (Ghostwriting Policy)

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Luis Cruz is responsible for revising the text and improving the translation of the article.

Sources of Funding for Research Presented in a Scientific Article or the Scientific Article Itself. No funding was received for conducting this study.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors state that they have no financial interests or personal relationships that could affect the work done in this study.